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ABSTRACT

This paper describes an analytical solution to a common problem in aptitude-treatment interaction (ATI). The researcher is often interested in the comparison between treatments for a large set of attributes. If this set is large, the chance of non-orthogonality is correspondingly large. In these circumstances the analysis and interpretation becomes equivocal. Using data from a study of contrasting teaching approaches in high school biology and thirteen attributes, a regression approach to the analysis is demonstrated. The redefinition of a new set of orthogonal variables is made on rational grounds rather than allowed to happen by default. (Author/BW)

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ATI WITH A LARGE SET OF NONORTHOGONAL ATTRIBUTE VARIABLES: A MULTIPLE REGRESSION SOLUTION

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1. INTRODUCTION

This paper describes an analytical solution to a common problem with the ATI approach. The researcher is often interested in the comparison between treatments for a set of attributes. If the set of attributes is large, the chance of nonorthogonality between them is correspondingly large. In these cases both analysis and interpretation become equivocal. One approach sometimes used is to undertake a series of two way anovas, one for each attribute. In this case interpretation is difficult, for if significant ATIs are observed between several correlated attributes, one is not certain whether the interaction is to be interpreted as unique to all of the attributes, or to their overlaps.

An alternative is to use multiple regression, but this does not, of itself, remove the problem. The researcher must still decide what to do about the overlaps between attribute variables. This paper will describe one solution to this problem, in the context of a study undertaken by Theobald (1977). Development of this solution is delayed until after a brief description of the study.

2. BRIEF DESCRIPTION OF THE STUDY

The study, which has been briefly reported elsewhere (Theobald, 1980), set out to investigate the relationships between student attributes, styles of teaching and outcomes in a secondary school biology course.

The Web of Life course is an Australian development of the Biological Sciences Curriculum Study (BSCS) materials for Years 11 and 12, and is committed to teaching strategies which emphasize the nature of scientific inquiry.

Eight teachers were selected who were teaching the same units of the Web of Life course, towards the same agreed ends, using the same instructional materials and the same recommended teaching strategies. However, as Yager (1968) pointed out, even when teachers are strongly committed to the strategies

advocated by the BSCS courses, they still maintain habitual patterns of interpersonal reaction and classroom technique which Klinckmann (1970) refers to as their personal teaching styles. By reference to a panel of judges the eight teachers selected were "known to be good teachers", but were believed to have contrasting natural teaching styles.

The classroom behaviour of these teachers was systematically observed and recorded over a year. Audiotapes were made of a sample of five one-hour lessons for each teacher, and annotated transcripts were analysed using a Category System for the Analysis of Teaching Styles (CATS) (Theobald, 1971). As expected, the teachers clustered into two groups but, contrary to expectation, one, originally believed to be in group one, was found to be a typical member of group two. Teachers in group one were found to differ characteristically from teachers in group two in that they carried out most of their teaching with individual students or small groups and asked more questions - both memory and open questions - whereas teachers in group two did most of their teaching by talking to the class as a whole.

Data were gathered on a number of attribute variables for the 146 students in the Year 11 biology classes of these teachers: general ability (Advanced Test B40, Australian Council for Educational Research (ACER), undated); 10 personality characteristics using scales from the Omnibus Personality Inventory (OPI) (Heist and Yonge, 1962); and two cognitive preference variables (Mackay, 1972).

Both cognitive and attitudinal outcomes were measured. The cognitive outcomes were measured by two of the ACER Biology Diagnostic and Achievement Tests (ACER, 1972). Test AD1, Diversity, consists almost entirely of questions requiring rote memory, whereas Test AI1, Interrelationships, requires skills of Comprehension, Application and Analysis (Bloom et al., 1956). The attitudinal outcomes were measured by an adaptation of four attitude scales

developed by Gardner (1972). This paper is concerned with a multiple-regression analysis of the relationship between the student attribute variables and teaching styles with respect to achievement on test AD1.

3. THE SOLUTION PROCEDURE

In regression terms, the data can be described as

$$Y_j = b_0 + b_1 T_j + b_2 I_j + \sum_{i=3}^{12} b_i PS_{(i-2)j} + \sum_{i=13}^{14} b_i CP_{(i-12)j}$$

$$+ b_{15} T_j.I_j + \sum_{i=16}^{25} b_i T_j.PS_{(i-15)j} + \sum_{i=26}^{27} b_i T_j.CP_{(i-25)j}$$

$$+ \epsilon_j \qquad \ldots(1)$$

where Y is the dependent variable, T is the treatment variable, I is the general ability variable, PS_1, PS_2 ... PS_{10} are the ten personality scale variables, and CP_1, CP_2 are two cognitive preference variables.

It can be seen that the interaction variables were defined by multiplication of the treatment variable with each attribute variable in turn. Quadratic terms were not included in the model because of the limited number of subjects involved. After the reduction in the number of independent variables the ratio of subjects to variables was only 18:1.

The intent of the analysis was to reduce this 'full' model to the simplest possible model which describes the relationships between the data without significant loss of information. Equation (1) contains all attribute and treatment variables and the first order attribute-treatment interactions. These variables were considered in a pre-determined order and those that failed to contribute significantly to the explained variance were eliminated at each successive step.

For the moment we will simplify this model by considering three variable sets imagining (temporarily) that each is a single variable. The three sets are: the general ability (I), which is a single variable, the personality variables (PS) and the cognitive preference variables (CP). These variables are not in-

dependent, that is they are nonorthogonal. This nonorthogonality can be represented in Venn diagram form (Figure 1)

(Figure 1 about here)

In the analysis, this nonorthogonality, represented here by the overlaps, needs to be reallocated in some way. This will be done by default if it is not done consciously. For instance, separate analyses of variance on each of these variables allocates the overlaps to each variable in turn (see Figure 2a).

If all three variables are included in a four way analysis of variance (with treatment) using the Overall, Spiegel and Cohen (1975) recommendation for nonorthogonal analysis of variance, all the overlaps are removed from each variable (Figure 2b). This makes the analysis very conservative.

A stepwise regression progressively allocates overlap to the highest correlate with the dependent variable, although the order of variables entered and so the nature of the particular variable tested depends on the particular sample result. (see Figure 2c).

(Figure 2 about here)

The important point here is that as part of the analysis the variables are redefined to produce orthogonal variables that are not identical to the original variables used.

Our philosophy is that the problem should be turned on its head; that the researcher should redefine the variables on rational grounds first and be explicit about the actual variables being tested. Our particular redefinition is now discussed.

First the main effects. General ability is known to be an important factor in learning. The other variables are only really of interest if they explain variance in the dependent variable that is not accounted for by general ability. Hence it makes sense to allocate all of the overlap of PS and CP with I to I.

This means that the variables PS' and CP' are redefined as those parts of PS and CP that are independent of I. This is represented in Figure 3a.

There are no obvious theoretical grounds for proposing an order between cognitive preference and personality. In this case it was decided to exclude the mutual overlap between these two variables. giving rise to the three orthogonal variables shown in Figure 3b.

(Figure 3 here)

I represents the total contribution of the general ability variable. CP" represents that part of CP that is independent of I and PS, that is the unqiue contribution of CP. PS" represents that part of PS that is independent of I and CP, that is, the unique contribution of PS.

There is some loss of statistical power in ignoring the overlap between CP' and PS' if this overlap is related to the dependent variable, but it was expected that this overlap would be small.

To summarise, the redefined orthogonal attribute variables are:

PS", personality scales controlled for cognitive preferences and general ability,

CP", cognitive preferences controlled for personality scales and general ability, and

I , general ability in its original form.

The testing of the redefined variables I, PS", and CP" can be achieved without the variables being transformed by comparison of the appropriate regression models. The models required are:

(a) $Y = f(T, I, CP, PS)$,

(b) $Y = f(T, I, PS)$,

(c) $Y = f(T, I, CP)$,

(d) $Y = f(T, I)$, and

(e) $Y = f(T)$.

Comparison of models (a) and (b) gives the influence of CP" on Y, comparison of models (a) and (c) gives the influence of PS" on Y, and comparison of models (d) and (e) gives the influence of I on Y.

The comparison of the total sums of squares of the various models permits the testing of the significance of loss in predictive accuracy accompanied by the dropping of terms from the full regression equation

$$F = \frac{(R_1^2 - R_2^2)/df_n}{R^2 \text{ due to error}/df_d} \qquad ...(2)$$

where R_1^2 and R_2^2 are the R^2 associated with the two models being compared.

The definition of the appropriate terms for R^2 due to error, df_n. and df_d will be discussed in a later section.

The interaction terms were considered in a similar way except for the (I x T) interaction. Unlike I, there is no reason to expect that the general ability x treatment interaction is generally related to cognitive or affective outcomes. Hence only the contribution of the 'unique' part of this interaction variable will be tested. Thus the redefined orthogonal interaction variables are:

(PS" x T), PS x T controlled for (CP" x T), (I" x T) and all main effects,

(CP" x T), CP x T controlled for (PS" x T), (I" x T) and all main effects,

and (I" x T), I x T controlled or (CP" x T), (PS" x) and all main effects.

These relationships are shown diagramatically in Figure 4.

(Figure 4 here)

The interactions are controlled for all main effects in the interests of parsimony. PS is a simpler variable than PS x T and the interaction term is only interesting if it 'explains' variance in the dependent variable that is not 'explained' by PS and T alone.

To this point in the discussion, PS and CP have been considered as single variables. The CP set consists of two approximately orthogonal cognitive

preference variables, reduced from four scales by an unfolding analysis (Coombs, 1958, 1964). Mackay (1972) states that Q-technique factor analyses conducted for sub-samples of the 9263 individuals in his study give an identical solution. Because of the possibility of slight overlap, the two cognitive preference scales were redefined as that part of the particular scale that was independent of the other. Personality attributes were measured in this study by 10 OPI scales. Four scales with a substantial number of items overlapping with other scales were omitted. There were substantial correlations between the 10 personality scales, and in order to resolve this non-orthogonality an orthogonal factor analysis was carried out. The consequent reduction in the number of variables is also favoured by Kerlinger and Pedhazur (1973) in their attack on the use of multiple regression as a shotgun technique. They advise that "before using many variables in multiple regression analysis, some attempt should be made to reduce the number through theory and factor analysis" (p.442). Four orthogonal factors were extracted by using Veldman's (1967) principal components analysis followed by varimax rotation and an eigenvalue cut off of 1.0. The first four roots extracted 72.6% of the trace. Although factor analysis solves the problem of nonorthogonality it often adds to difficulties in interpretation. Fortunately in this study the interpretation of the four factors was not unduly difficult. The factor matrix is relatively simple with 6 of the 10 scales having only one significant non-zero loading.

The redefinition of the attribute variables and the attribute-treatment interaction terms produces the following set of redefined orthogonal variables that were tested in the analysis:

$PF"_1$, scores on personality factor 1 controlled for the other three personality factors ($PF"_2$, $PF"_3$, $PF"_4$), the two cognitive preference scales

scales ($CP"_1$, $CP"_2$), and general ability (I). (It is stated here and below in this way in order to be consistent with the regression models actually tested. In fact the four personality factors are orthogonal and so there is no effect in controlling for them).

$PF"_2$, scores on personality factor 2 controlled for the other three personality factors ($PF"_1$, $PF"_3$, $PF"_4$), the two cognitive preference scales ($CP"_1$, $CP"_2$), and general ability (I).

$PF"_3$, scores on personality factor 3 controlled from the other three personality factors ($PF"_1$, $PF"_2$, $PF"_4$), the two cognitive preference scales ($CP"_1$, $CP"_2$), and general ability (I),

$PF"_4$, scores on personality factor 4 controlled for the other three personality factors ($PF"_1$, $PF"_2$, $PF"_3$), the two cognitive preference scales ($CP"_1$, $CP"_2$) and general ability (I),

$CP"_1$, scores on cognitive preference scale 1 controlled for $CP"_2$, the four personality factors ($PF"_1$, $PF"_2$, $PF"_3$, $PF"_4$), and general ability (I),

$CP"_2$, scores on cognitive preference scale 2 controlled for $CP"_1$, the four personality factors ($PF"_1$, $PF"_2$, $PF"_3$, $PF"_4$), and general ability (I),

I, the raw scores on the ACER B 40 test,

scores on personality factor 1 x treatment score controlled for ($PF"_2$ x T), ($PF"_3$ x T), ($PF"_4$ x T), ($CP"_1$ x T), ($CP"_2$x T), (I" x T), and all main effects,

($PF"_2$ x T), scores on personality factor 2 x treatment score controlled for ($PF"_1$ x T), ($PF"_3$ x T), ($PF"_4$ x T), ($CP"_1$ x T), ($CP"_2$ x T), (I" x T), and all main effects,

($PF"_3$ x T), scores on personality factor 3 x treatment score controlled for ($PF"_1$ x T), ($PF"_2$ x T), ($PF"_4$ x T), ($CP"_1$ x T), ($CP"_2$x T). (I" x T), and all main effects,

($PF"_4 \times T$), scores on personality factor 4 x treatment score controlled for ($PF"_1 \times T$), ($PF"_2 \times T$), ($PF"_3 \times T$), ($CP"_1 \times T$), ($CP"_2 \times T$),($I" \times T$), and all main effects,

($CP"_1 \times T$), scores on cognitive preference scale 1 x treatment score controlled for ($PF"_1 \times T$), ($PF"_2 \times T$), ($PF"_3 \times T$), ($PF"_4 \times T$), $CP"_2 \times T$), ($I" \times T$) and all main effects,

($CP"_2 \times T$), scores on cognitive preference scale 2 x treatment score controlled for ($PF"_1 \times T$), ($PF"_2 \times T$), ($PF"_3 \times T$), ($PF"_4 \times T$), ($CP"_1 \times T$), ($I" \times T$), and all main effects, and

($I" \times T$), general ability score x treatment score controlled for ($PF"_1 \times T$), ($PF"_2 \times T$), ($PF"_3 \times T$), ($PF"_4 \times T$), ($CP"_1 \times T$), ($CP"_2 \times T$), and all main effects.

As a result of this redinition of variables the full regression model now becomes:

$$Y_j = b_0 + b_1 T_j + b_2 I_j + \sum_{i=3}^{6} b_i PF"_{(i-2)j} + \sum_{i=7}^{} b_i CP"_{(i-6)j}$$

$$+ b_9 T_j.I"_j + \sum_{i=10}^{13} b_i T_j.PF"_{(i-9)j} + \sum_{i=14}^{15} b_i T_j.CP"_{(i-13)j}$$

$$+ j \qquad \ldots(3)$$

4. NON-ORTHOGONALITY BETWEEN INTERACTIONS AND MAIN EFFECTS

The strategy used to test interaction terms so that they are orthogonal to their related main effects has already been considered. However, an essentially similar problem exists in testing for main effects when significant interactions have been found. For example, if the effect of ($PF"_1 \times T$) was found to be significant, then it must remain in the full model when testing for main effects.

When the $PF"_1$ main effect is tested, its overlap with ($PF"_1$ x T) will remain in the full model so that only $PF"_1$ controlled for ($PF"_1$ x T) will be tested. This problem can be overcome if the definiton of T is such that ($PF"_1$ x T) is actually independent of $PF"_1$. This independence is achieved in the computation of orthogonal contrasts in analysis of variance by assigning the value 1 to subjects in one treatment group and the value -1 to subjects in the other: a procedure described by Cohen (1968) as contrast coding. The simulation of the equal cells analysis of variance by multiple regression analysis requires orthogonality between all terms of the regression equation. Where cells are equal, there is essential agreement by Overall and Spiegel (1969, 1973), Gocka (1973) and Overall, Spiegel, and Cohen (1975) that the nominal scale variables should be coded (1, 0,..., -1), which in the case of contrasting treatments is (1, -1). When this coding is used, the product variable (PF" x T) will be independent of PF". When the cell numbers are not equal the (1, O,..., -1) coding does not produce orthogonality (Gocka, 1973; McArthur, Fraser, & West, 1975). In this investigation the difference in cell size was not large (79, 67) and although the (1, -1) coding leaves a slight correlation between the terms, the consequent loss of power is slight.

In retrospect, we think that Gocka (1973) coding would be more appropriate although it should be noted that Overall, Spiegel and Cohen do not share this view.

5. THE APPROPRIATE ERROR TERM

The algorithm used to complete F was given in equation 2. The denominator contains the R^2 due to error. The usual procedure in analysis of variance is to include all effects, whether significant or non-significant, in the computation of the error term. In multiple regression terms this means using $1 - R^2_{full}$ where R^2_{full} is associated with the model containing all terms

(Overall & Spiegel, 1969, p.316; Kim & Kohout, 1975, p.337). When a large number of terms is involved, even if they are not significant, they can act to substantially recuce the error term and so inflate the value of F.

In this analysis the full regression model was used to compute the error term for the test of interaction effects. however, at the completion of that analysis the strategy suggested by Rawlings (1973) was followed: the full model was revised so that it included only those interaction terms that were significant. This revised model was used to compute the terms for the main effects analysis.

Thus the algorithm for the interaction effects was

$$F = \frac{(R_A^2 - R_B^2)/(V_A - V_B)}{(1 - R^2_{full})/(N - 1 - V_{full})} \qquad ...(4)$$

where, models A and B are the models being compared, the full model is the model described by equation 3, V_A is the number of variables in model A, V_B is the number of variables in model B, and V_{full} is the number of variables in the full model.

The algorithm used for testing main effects was

$$F = \frac{(R_A^2 - R_B^2)/(V_A - V_B)}{(1 - R_C^2)/(N - 1 - V_C)} \qquad ...(5)$$

where, model C contains all main effects and only those interaction terms found to be significant, and V_C is the number of variables in model C.

6. THE ANALYSIS OF SOME RESULTS FROM THE STUDY

A number of dependent variables were measured. The analysis described here refers to one of the achievement tests, the AD1 concerning diversity of living organisms.

(a) Interactions

The results are shown in Table 1. The full model for interactions i.e. Model A is described by equation (3). Model B has each of the interaction terms in turn removed from model A.

TABLE 1 about here

At this stage the full model had been reduced to

A D I = f (all main effects, PF_4"xT, Cp_2"xT) ...(6)

This model (for which R^2 = .36) became the model A for the main effects analysis (see equation 5).

(b) Main effects

The results are shown in Table 2. The comparison of models was guided by the decisions described in section 3.

TABLE 2 about here

This leads to the following final equation which most parsimoniously described the data.

$$Y_{ADI} = 7.70 - 0.60\ PF_3 - 0.87\ PF_4 - 4.21T + 0.15\ I + 0.27\ (T \times CP^2) + 0.63\ (T \times PF_4)$$

with $R^2 = 0.34$

which reduces to

$$Y_{ADI} = 3.49 - 0.60\ PF_3 - 0.24\ PF_4 + 0.15\ I + 0.27\ CP_2$$

for T = +1, i.e. individual centred teaching style

and $Y_{ADI} = 11.91 - 0.60\ PF_3 - 1.50\ PF_4 + 0.15\ I - 0.27\ CP_2$

for T = -1, i.e. class centred teaching style.

In order to examine the interactions, the mean values for I and PF were substituted into these equations. The resultant equations are plotted (3 dimensional plot) in Figure 4 organisms.

Before describing this result, the nature of the variables is des . The

ADI test is a test of knowledge of classification of plants, animals and micro organisms. It calls, almost exclusively, for memory alone. The cognitive preference scale (CP_2) measures a preference for understanding principles (high score) rather than for rote learning (low score). The personality measure (PF_4) was a measure of open/closed mindedness. High scorers tend to be dogmatic, conservative and orthodox religious believers. Low scorers tend to be sceptical of fundamental beliefs, independent of traditional authority, and having a preference for being and working alone.

[Figure 4 here]

The interaction is shown in Figure 4. Treatment 1 (individual centred teaching style) is better for students with a medium to high preference for learning principles rather than rote learning and/or for students who tend to be closed minded. Treatment 2 (class centred teaching style) is better for students who prefer rote learning and who tend to be open minded. That is for students who are both open minded and have a preference for rote-memory, class centred teaching leads to greater achievement on what is basically a memory task; for closed minded students and those with a preference for principles and generalizations in biology, the individual centred teaching is better for a memory task.

In explanation it is suggested that the individual centred teaching gives assistance to those who suffer some inability to accept the new information readily, and to those whose cognitive preference is not congruent with the learning task, but has an 'over-kill' effect on those who are able to accept the information readily and for whom the task is congruent with their cognitive preference.

7. CONCLUDING COMMENTS

The analysis described is a useful and simply executed method of dealing

with nonorthogonality among a set of attribute variables in an ATI study. We do not intend to be prescriptive in any sense. Each study is individual in its analytic needs. The philosophy we want to preach is that in any nonorthogonal design the analysis involves a redefinition of the variables, allocating their overlaps in some way to produce orthogonal variables. We propose that this redefinition should be done deliberately by the researcher rather than left to the whims of the analysis.

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TABLE 1 Testing of interaction effects

Variable being tested	R^2_A	R^2_B	F
I"xT	0.3719	0.3716	0.06
PF_1"xT	0.3719	0.3718	0.02
PF_2"xT	0.3719	0.3706	0.27
PF_3"xT	0.3719	0.3705	0.29
PF_4"xT	0.3719	0.3459	5.38 *
CP_1"xT	0.3719	0.3608	2.30
CP_2"xT	0.3719	0.3322	8.22 **

* P < .05; ** P < .01

TABLE 2 Testing of main effects

Variable being tested	R^2_A	R^2_B	F
PF_1"	0.3589	0.3518	1.5
PF_2"	0.3589	0.3580	0.19
PF_3"	0.3589	0.3383	4.34 *
PF_4"	0.3589	0.3150	9.24 **
CP_1"	0.3589	0.3587	0.04
CP_2"	0.3589	0.3573	0.34
Treatment	0.3589	0.3318	5.71 *
I	0.2858	0.1656	25.31 ***

* P < .05; ** P < .01; *** P < .0001
(In each case R^2_C = 0.3589).

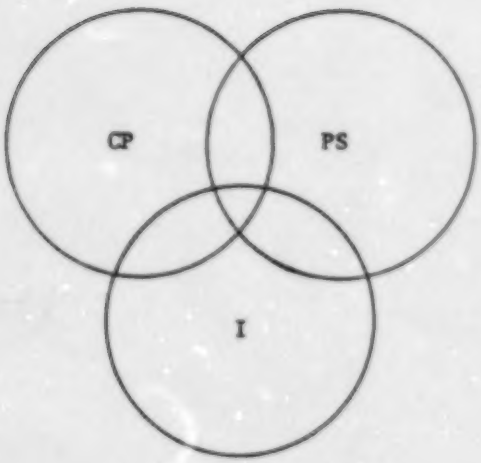

Figure 1 The non-orthogonality of general ability, cognitive preference, and personality attributes.

Figure 2(a) Orthogonal variables using separate 2-way anovas (with treatment).

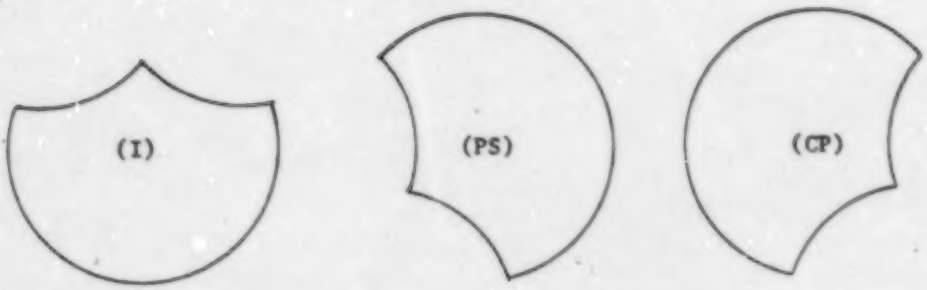

Figure 2 (b) Orthogonal variables using 4-way anova (with treatment).

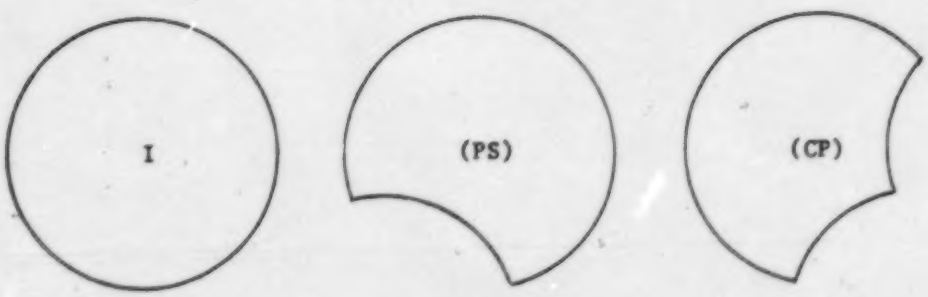

Figure 2 (c) Orthogonal variables using stepwise regression.

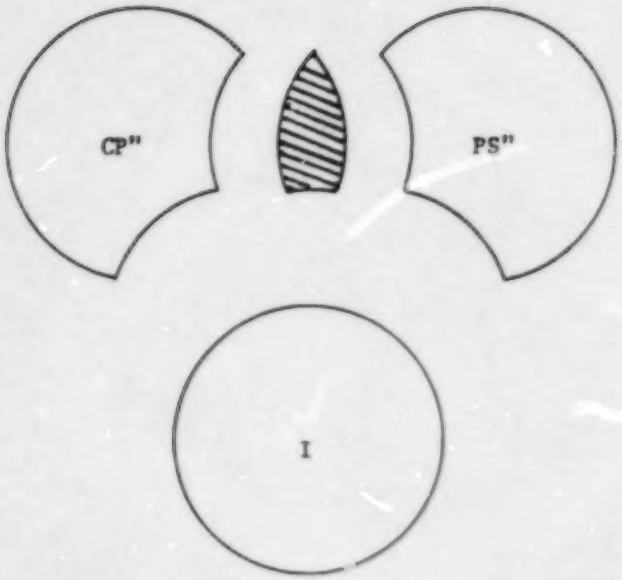

Figure 3a Redefinition of orthogonal attribute variables.

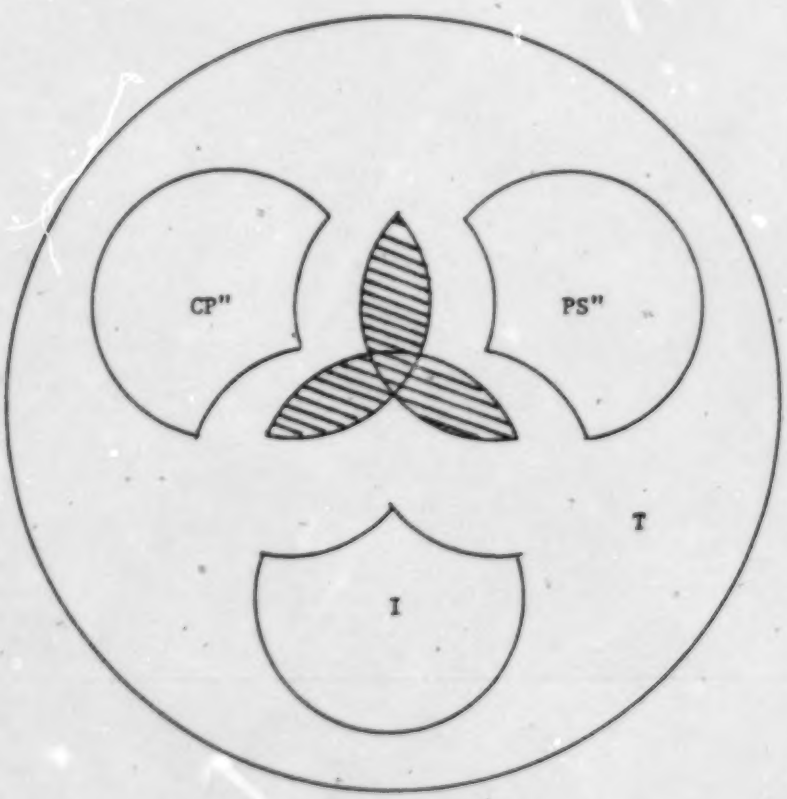

Figure 3b The orthogonal attribute-treatment interaction variables.

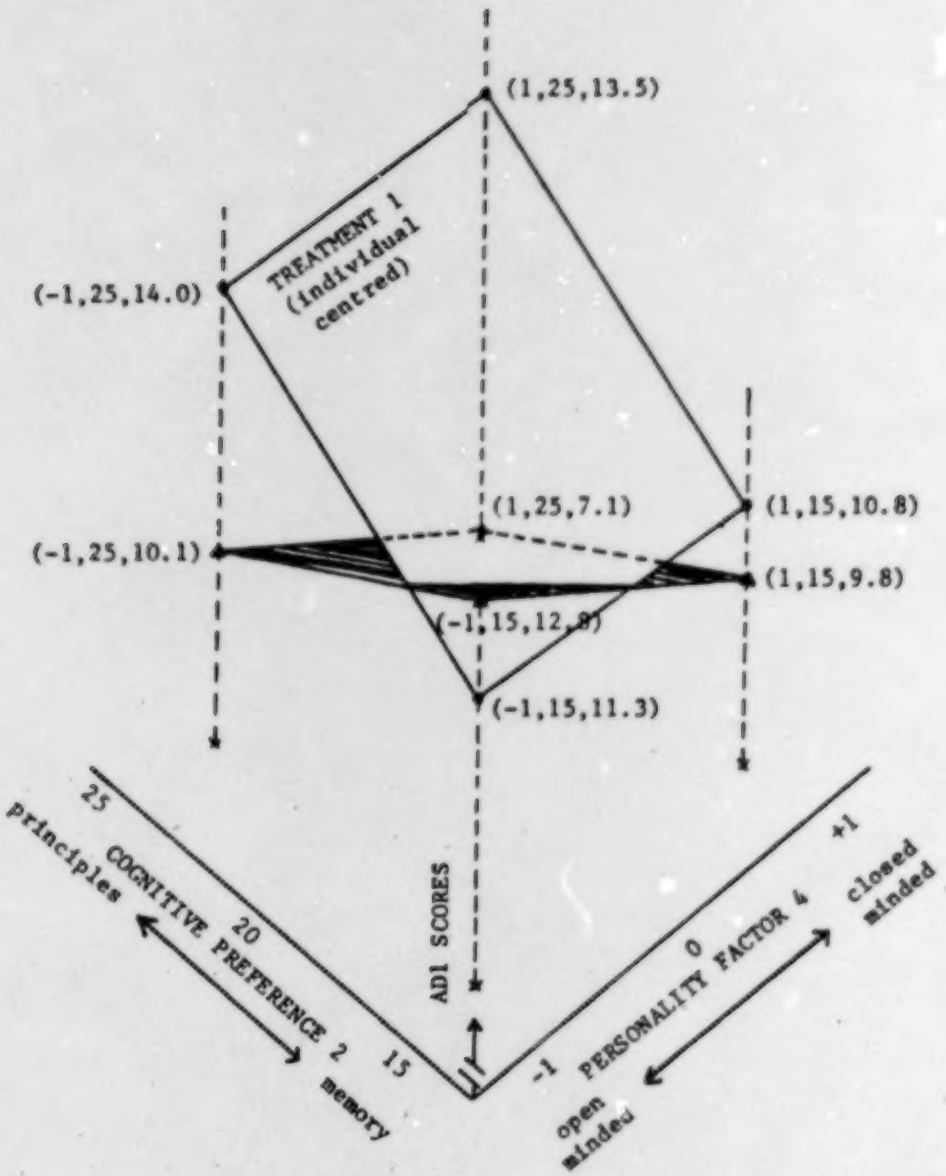

Figure 4 Combined plot of personality factor 4 scores and cognitive preference 2 scores against AD1 scores.